OPTIMIZATION OF INTELLIGENT MUNITION WARFARE USING AGENT-BASED SIMULATION SOFTWARE AND DESIGN OF EXPERIMENTS METHODOLOGY

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ABSTRACT

The era of "dumb" munitions is coming to a close for the US arsenal. The new generation of ground-based munitions are much more like sentinels which guard a region and have an "intelligent" capability to select targets, cycle on or off and provide the primary killing mechanism for a number of vehicles caught in the kill-zone. Thus, it is useful to study and attempt to model through equations and simulation the interaction between enemy agents and these new munitions.

The objective of this paper is to propose use of agent-based modeling software with Design of Experiments methodology to evaluate placement patterns for US intelligent munitions in an effort to optimize their performance. This study introduces MANA, the agent-based modeling software, and presents the results from a series of simulation trials to analyze and compare the efficacy of three different placement patterns for the Hornet Wide Area Munition over a range of densities. The results of the study indicate in general that agent-based modeling software and Design of Experiments methodology may be very useful in optimizing strategies for munition emplacement. A specific result from the case study used herein indicates that there are more optimal options for emplacement of the munitions for a disruption-type effect than what is currently recommended based upon doctrine.

The authors utilized both Central Composite Design and Latin Hypercube sampling methods to develop two independent test matrices for use in carrying out the simulations and comparing results. The experimental results were then used to develop a 2nd order Dual Response Surface for use in optimizing the design.

1. INTRODUCTION

Ground-based munition warfare has not received extensive analytical attention in the course of the century since Lanchester's Equations for Warfare were originally defined. Generally, the number of vehicles or individuals killed by ground-emplaced munitions was relatively small compared to those killed by direct or indirect fire weapon systems. The primary purpose for these types of munitions has always been to shape the existing terrain and ideally place enemy forces into positions where direct or indirect fire weapon systems may be brought to bear to wreak the true destruction. This era of simple or dumb munitions as a weapon in the friendly arsenal is nearing an end for US forces. The new generation of munitions are much more like sentinels which guard a region and have an "intelligent" capability to select targets, cycle on or off and provide the primary killing mechanism for a number of vehicles caught in the kill-zone.

1.1 Hornet, Wide Area Munition (WAM)

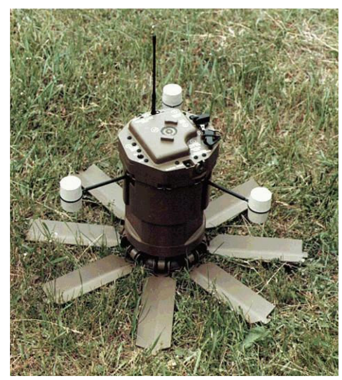

Figure 1: Hornet Wide Area Mine [1]

The M93 Hornet smart munition represents the future of intelligent munition warfare. The ground-based munition is a self-aware, communicating and sensing, top-attack system designed to attack vehicular targets at ranges up to 100m. Targets could be anything from heavy trucks to tanks. Currently these devices must be hand-emplaced (HE-WAM) and are remotely controlled to cycle them into a sleep mode for passage of friendly forces or to turn them off for collection and reuse elsewhere. The sensor and communication suite not only increases the likelihood of an enemy kill, it decreases the likelihood of fratricide. Future versions are planned to enable remote delivery by aircraft or artillery (DA-WAM) [2]. The munition itself consists of a ground base (Figure 1) which is the primary sensing unit and launcher for the sublet, and the sublet itself, which provides the killing stroke. Upon acquisition of an enemy vehicle and after computing a kill solution, the sublet is launched on a trajectory that ends above the target, at which point it fires an explosively-formed penetrator (EFP) into the top of the equipment (Figure 2).

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Figure 2: Hornet sub-munition is fired over the top of a target tank (right). The EFP is fired (center) from the sub-munition into the top of the target (left) [1]

In this study, the authors evaluated the current doctrine for placement of a Hornet field in a 1 km square “area disrupt” munition field. Current doctrine calls for emplacing 20 munitions in an “X” pattern as indicated in Figure 3 [3].

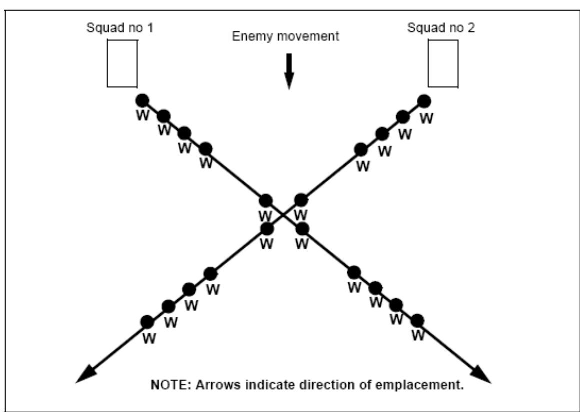

Figure 3: Large-area Hornet disruption field

1.2 Map Aware Non-Uniform Automata (MANA) Software

The MANA software was developed in the form evaluated for this test in 2001 by M.K. Lauren and R.T. Stephen for New Zealand’s Defence Technology Agency, DTA and is an outgrowth of collaborative work between the software authors and researchers and the US Marine Corps which has been developing simulation software that attempts to model complex behavior without using a top-down, rules-based, deterministic approach [4]. This research is part of an attempt to answer the concern that JANUS and software like JANUS will never approach reality, since it is generally too deterministic and has such a strict hierarchy of rules that the human dynamic is not sufficiently factored into the model. References [5-7] describe in detail the deterministic methods used to model force on force interaction. The software authors of the MANA software specifically cite work done by DR Andy Ilachinski through the Einstein Project as impetus for their own efforts [8].

MANA is a Cellular Automaton (CA) model which is a subset of a new class of models referred to as Agent-Based Models (ABMs). These models attempt to allow agents, which may be variously soldiers or vehicles, to exhibit decision-making behavior given a general mission set of rules for routes and combat. Agents may be programmed with a personality (Fig 4) that is more or less aggressive and given varying march rates and varying degrees of weapon capability and stealth capability. Once a squad of agents (1-255 agents) has encountered enemy forces, the personality of the entire squad may be altered to reflect that the unit is now under attack. For example, the march rate may decrease, the randomness of movement may be increased to allow the soldiers to run and dodge enemy fire. See Figure 5 for an example of the terrain map and Graphic User

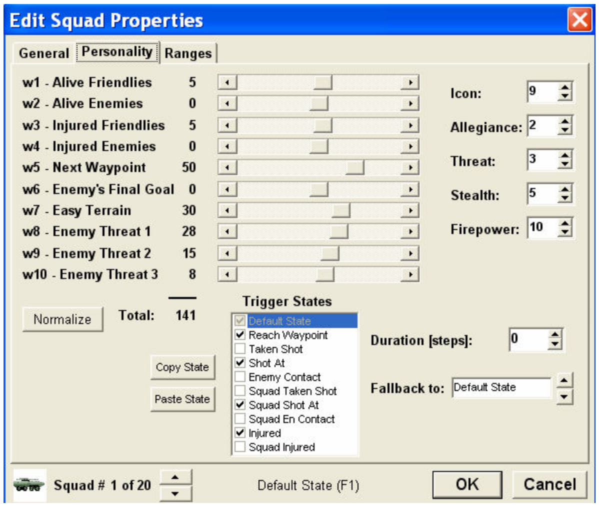

Figure 4: MANA input screen for squad personality.

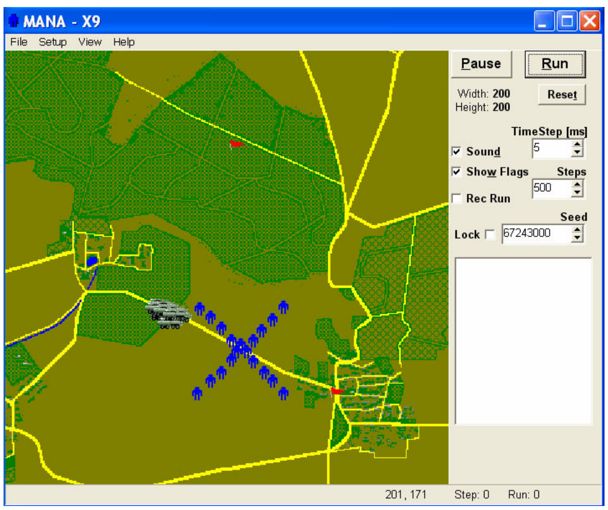

Figure 5: MANA battlefield with X-Pattern minefield

Interface (GUI) used for the set of experiments discussed in this paper. Yellow roads are indicated as easy terrain, green provides no obstacle for movement. Obstacles may be emplaced as gray patches.

A user of the software may program a few basic capabilities, create a simple mission for the various units represented in the simulation, then let them go. Since each simulation is based upon a different random seed number, a surprising number of outcomes are possible. Over a large number of trials, one may generally see a trend in behavior emerge from the local interactions of agents. Data may be tracked as number killed per each side over a large number of runs, or each experiment may be recorded to track more specific details such as the time of each death and when enemy agents saw each other.

Movement within the model by each agent is based upon a penalty calculation. Each agent may move in one of six directions from its current location or stay put and will choose to do so after evaluating the penalty associated with each possible move. The move which gives it the lowest penalty is the move that will be made. Personality weightings such as aggressiveness toward the enemy, or a desire to flee the enemy plus input from local sensors and its global situational awareness map will all provide factors in the penalty calculation. The user can also program in a lower or higher degree of randomness to the movement as well to assist in keeping an agent from literally getting boxed into a corner.

In general, this relatively new software is extremely flexible and designed to primarily allow a user to quickly explore different possibilities for war-fighting scenarios. The key is understanding that essentially the software simulates human behavior at a simplistic level by applying a similar approach to action. Soldiers are taught a few key behaviors and learn a set of battle drills to assist them in reacting during combat. This relatively small set of learned behaviors derives an array of complex actions and interactions. Although this software was not developed with a ground-based munition warfare scenario in mind, it is clear that future testing could make use of this or like software that has been revised to handle additional scenarios.

2. STUDY OBJECTIVE

The objective of this study and paper is to illustrate and propose use of this agent-based modeling software with Design of Experiments (DoE) methodology to evaluate placement patterns for US intelligent munitions in an effort to optimize their performance. This study presents the results from a series of simulation trials to analyze and compare the efficacy of three different placement patterns for the WAM over a range of densities. The specific case study chosen for evaluation was to attempt to determine if the current doctrine for placement of the WAM in a one square kilometer "disrupt" pattern is optimal. Disruption fields are generally placed forward on the battlefield to disrupt and delay enemy formations. This type of pattern is most often used to cause the enemy to slow enough to create a target-rich environment for air or artillery-delivered assets to attack the enemy formations prior to entrance into a main battle area.

3. METHODOLOGY

The authors used the Robust Design approach pioneered by Dr. Genichi Taguchi to conduct design and improvement for Japanese industry in the 1960s-1980s. This approach is an eight-step process as shown below [9]:

Planning the Experiment

1. Identify the main function, side effects and failure modes.
2. Identify noise factors and the testing conditions for evaluating the quality loss.
3. Identify the quality characteristic to be observed and the objective function to be optimized.
4. Identify the control factors and their settings.
5. Design the matrix experiment and define the data analysis procedure.

Performing the Experiment

6. Conduct the matrix experiment.

Analyzing and Verifying the Experimental Results

7. Analyze the data, determine optimum levels for the control factors, and predict performance under these levels.
8. Conduct the verification experiment and plan future actions.

3.1 Control and Noise Factors

Initially two potential main functions were identified for evaluation: delay of enemy agents in the munition field and number of enemy agents killed in the munition field. Because the primary function of the field is to delay opposing forces or encourage them to move elsewhere, the first function is the main function. The second was added because these new types of munitions are different from the older generation in that they may be able to provide a primary killing function as well. It was also easy to evaluate with no additional cost given the set-up of this particular simulation system.

Because this entire set of experiments is run in simulation, the main noise factors are related to the operation of the simulation. Primarily, an operator has to stop the timer manually when the first enemy agent reaches the objective to note and record the time at which this occurs before releasing the simulation to complete its 500 time steps. The remaining data are captured primarily in recorded output by the simulation. Stopping the timer can be a little slower or a little faster during each run as a person is watching and hitting a pause button. To reduce the impact of the "stop watch" noise factor, the author was the simulator operator for the entire set of simulations, and each experiment was run 30 times whereby a slightly slow or fast trigger finger is less likely to impact the overall mean or standard deviation. Future versions of software could be written to build in a timer function.

Based upon the main functions identified as delay of agents in the munition field and lethality of the munition field, the author developed three Measures of Effectiveness (MoE):

1. Time delay of enemy agents in the munition field (time steps from start of simulation until the first enemy agent reaches the objective)
2. Number of enemy agents on the objective at the completion of 500 time steps.
3. Number of enemy agents killed in the munition field at the completion of 500 time steps.

The control factors to be evaluated are munition field width (b_1), depth (b_2) and pattern (b_3). To achieve a 2[nd] order math model as in Eqn 1, three levels for each setting are necessary.

Maximize:

$$y = a_0 + \sum_{i=1}^{3} a_i * b_i + \underbrace{\sum_{i=1}^{3}\sum_{j=1}^{3} a_{ij} * b_i * b_j}_{i<j} + \sum_{i=1}^{3} a_{ii} * b_i^2 \qquad (1)$$

subject to: $750\text{m} \le b_1 \le 1250\text{m}$
$750\text{m} \le b_2 \le 1250\text{m}$
$b_3 \in$ {Row, X Pattern, Random Scatter}

Since the current baseline munition field is sized at 1000m x 1000m. The width and depth settings will be evaluated from 750m up to 1250m. The alternate patterns are chosen as real alternates that have been used in military tactical munition emplacement.

3.2 Experimental Matrix Design

A Central Composite Design (CCD) for the test matrix was selected as this was optimum for requiring the least amount of experiments while still including degrees of freedom for the error. A full factorial array would require $3^k=3^3=27$ experiments, where k is defined as the number of levels to be tested. A Taguchi Orthogonal Array would provide no cost savings as the L_{27} array would be required to handle the ten degrees of freedom necessary to produce a 2[nd] order math model [9]. The corresponding CCD test matrix requires 15 experiments as shown in Table 1. The factor settings are coded to values of -1, 0 and 1 to enable the post experiment data analysis. The CCD used for this experiment is a face-centered-design. The first eight experiments are based upon sampling the design space extremes using a 2^k full factorial orthogonal array design. Then, intermediate points are sampled in the last six experiments with the center point sampled in experiment nine [10]. Once the experiments are completed, the

results are analyzed using regression analysis to develop a best-fit, 2nd order math model [11].

Table 1: Central Composite Design Test Matrix

	CCD Main Columns		
Factors / Experiments	Main Factors		
	b_1 (Width m)	b_2 (Depth m)	b_3 (Pattern)
1	750	750	Row
2	1250	750	Row
3	750	1250	Row
4	1250	1250	Row
5	750	750	Random
6	1250	750	Random
7	750	1250	Random
8	1250	1250	Random
9	1000	1000	X
10	750	1000	X
11	1250	1000	X
12	1000	750	X
13	1000	1250	X
14	1000	1000	Row
15	1000	1000	Random

To provide additional data points based upon an alternate sampling method, a Random Latin Hypercube sampling method was utilized to develop a second, fifteen-experiment matrix for comparison purposes. In the Latin Hypercube methodology, the design space is parsed into p^n bins of equal probability, where p represents the number of sample points to be taken and n is the number of design variables. (The ranges for b_1 and b_2 in this problem were parsed into five uniform probability bins.) The p samples are then selected from the design space such that for all two dimensional projections from the design space, there is exactly one sample from any given intersecting row and column [12]. Since b_3 is a discrete variable with only three levels, the authors modified the approach by creating a 2-dimensional Latin Hypercube (LH) array for b_1 and b_2. This array was then tested three times for each of the three level settings from b_3. The two-dimensional array shown in Table 2 was developed through the use of the LHS function in MATLAB along with a program to convert the output into the desired ranges for study [13]. The LH test array is shown in Table 3.

Table 2: Latin Hypercube Sample Design for n=2 Design Variables

	Latin Hypercube for n=2					
b2	1250				X	
	1125	X				
	1000			X		
	875					X
	750		X			
		750	875	1000	1125	1250
	b1					

Table 3: Latin Hypercube Design for Testing

	LHS Main Columns		
Factors / Experiments	Main Factors		
	b_1 (Width m)	b_2 (Depth m)	b_3 (Pattern)
1	750	1125	Row
2	875	750	Row
3	1000	1000	Row
4	1125	1250	Row
5	1250	875	Row
6	750	1125	X
7	875	750	X
8	1000	1000	X
9	1125	1250	X
10	1250	875	X
11	750	1125	Random
12	875	750	Random
13	1000	1000	Random
14	1125	1250	Random
15	1250	875	Random

3.3 Simulation Experimental Set-up

The simulation portion of this study consisted of creating a scenario whereby a formation of fifteen enemy vehicles traveling along a route would encounter a munition field between their start and end points. The Random Scatter munition field, as the name implies, was randomly different for each trial based upon a new random seed number generated at the beginning of each trial by MANA. The Row and Random Scatter munition fields were selected as alternatives for comparison to the X-pattern because they are easy to emplace under tactical conditions by vehicle (Row) or air-delivery system (Random Scatter). Determining that a more complex shape works better would serve little purpose other than to make it difficult to emplace quickly in combat. The size is approximate and based upon scaling the munition field size to the size of the terrain allowed by MANA for the entire battlefield (up to 500 x 500 cells). The default battlefield size of 200 x 200 cells was used to retain use of the default terrain bitmap. With this scale, 1 km is 40 cells or 1 cell equals 25 meters. The terrain bitmap provides color and a sense of scale primarily. The yellow represents roads and is considered an easier path to follow when agents are making movement decisions. Each experiment consisted of 30 simulation trials against each munition field to record casualties and estimate the time spent in the munition field until the first vehicle reached the objective point.

Although the current engineering warfare doctrine calls for 20 "Blue" or friendly munitions arrayed in five clusters along two legs as indicated in Figure 3, only 19 munitions were placed in the simulation trials. Due to an

apparent bug, the maximum number of squads that could be programmed with this software version was 20, even though the documentation indicated otherwise. Thus, there were 19 "squads" of munitions consisting of one agent per squad and a squad of 15 enemy "Red" vehicles. Because each munition was placed in a particular location on the terrain, it required identification as a separate squad to dictate location. This was not a problem with the random scatter munition field since it was possible to generate one squad of 19 Blue agents and place them randomly within the munition field boundaries. Their number remained 19 to retain the ability to compare results with the other patterns. Future studies should be completed with software tailored to better fit the specific requirements of this type of munition warfare study.

Each trial was stopped after 500 time steps. Generally, most of the action ended well before the 500 time steps. If there were any vehicles still alive at that point, they had either escaped the munition field or they were "stuck" in the munition field and unable to decide a way out within the 500 time steps. This "indecision" is not unrealistic given that a real vehicle driver might be hesitant to move after seeing 12 of 15 vehicles destroyed in relatively short order and with little warning as they moved into the area with these munitions.

To establish a baseline for the delay caused by the munitions, a separate experiment consisting of thirty trials that allowed the Red vehicles unopposed movement from the start point to the end objective was completed.

The munitions were given a high Probability for a Single Shot Kill (P_{SSK}) with a low observability probability. Once the munition fired, the simulation changed its state to a dead state, so that it could not continue firing.

The Red vehicles, were given a constant movement rate of 25 m/s (1 cell/time step) with a high observability profile, P_{seen}=.90. A series of waypoints leading from the squad start point to the final objective was provided to guide movement. Each vehicle had a P_{SSK}=.10 since it is shooting a large caliber machine-gun on the move at a small target on the ground. The default personality state for each member of the Red squad was a high desire to get to the final objective along the plotted waypoints and a desire to seek out enemy forces. Once the squad of vehicles or individual vehicle began taking shots, the personality state shifted to reflect a more cautious attitude. Vehicles lost desire to stick to the original path in a rigid fashion, they were drawn toward surviving members of the squad without bunching-up into a target group, and they attempted to avoid munitions when they could detect them. The goal was to create a company of recon vehicles that would attempt to get to their objective, seeking bypasses as necessary.

4. EXPERIMENTAL RESULTS

Since each experiment consists of 30 trials in an effort to get a more accurate mean for each MoE, the authors decided to utilize more of the available data to build Dual Response Surfaces for use in the data analysis. By developing equations for both the mean and standard deviation, variability could be addressed in the designs. This changed the initial math model shown in Eqn 1 to the one illustrated in Eqn 2.

Maximize:

$$y_\mu = a_0 + \sum_{i=1}^{3} a_i * b_i + \underbrace{\sum_{i=1}^{3}\sum_{j=1}^{3} a_{ij} * b_i * b_j}_{i<j} + \sum_{i=1}^{3} a_{ii} * b_i^2 \qquad (2)$$

subject to: 750m$\leq b_1 \leq$1250m
750m$\leq b_2 \leq$1250m
$b_3 \in$ {Row, X Pattern, Random Scatter}
$y_\sigma \leq$max desired standard deviation

where,

$$y_\sigma = c_0 + \sum_{i=1}^{3} c_i * b_i + \underbrace{\sum_{i=1}^{3}\sum_{j=1}^{3} c_{ij} * b_i * b_j}_{i<j} + \sum_{i=1}^{3} c_{ii} * b_i^2$$

The statistical analysis for this study was based upon use of the sample mean (Eqn 3) and standard deviation (Eqn 4) as reasonable approximations for the population mean and standard deviation. The authors used standard regression analysis to develop a response surface and determine a coefficient of determination, R^2, (Eqn 5) to assess goodness of fit [14].

$$\mu \approx \overline{\mu} = \frac{1}{n}\sum_{i=1}^{n} x_i \qquad (3)$$

$$\sigma \approx \overline{\sigma} = \left(\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \mu)^2\right)^{\frac{1}{2}} \qquad (4)$$

$$R^2 = \frac{\sum_{i=1}^{n}(\hat{x}_i - \overline{\mu})^2}{\sum_{i=1}^{n}(x_i - \overline{\mu})^2} \quad \begin{array}{l} where, \\ \hat{x}_i \equiv predicted\ value \\ \overline{\mu} \equiv estimated\ mean \\ x_i \equiv observed\ value \\ n \equiv number\ of\ samples \end{array} \qquad (5)$$

The results from the simulation tests are summarized in Tables 4 and 5. Table 4 shows the average mean and average standard deviation for the experiments by pattern type as portrayed in the Time Delay results column. Since the number of time steps is simply an indicator of relative time, all of the results are normalized with respect to the Mean Unopposed Baseline time. It is clear from the mean values that the Row pattern performed

much better than the other two patterns as the time for the first agent to traverse the area with munitions was almost five times the time required for the unopposed march. It is also clear that the Random Scatter pattern performed slightly better than the current X-pattern.

Table 4: Initial Results from Experimental Data Analysis for CCD and LHS Test Matrices

Time Delay in Obstacle (normalized)	**CCD matrix results**		**LHS matrix results**	
	Average Mean	**Average Std Dev**	**Average Mean**	**Average Std Dev**
Row Pattern	4.78	1.28	4.55	1.26
X-Pattern	3.74	1.04	3.57	1.21
Random Scatter Pattern	3.98	1.38	3.87	1.36
Baseline Unopposed March	1.00	.02	--	--

The standard deviation for the Row pattern was higher than the X-Pattern. The standard deviation for the Random Scatter pattern (as tested) was the highest, which is not unexpected since the pattern is completely random from one trial to the next within a given experiment.

Table 5 shows the regression results of this exercise for both the CCD and the LHS test matrices for each MoE. In reviewing the data, two of the three MoE had low R^2 values indicating that the regression analysis was not a good fit for the data. This could be caused by the order of the math model not being high enough or a lack of interaction by the selected study variables with the observed output. There was a very good fit for the first MoE, Time Delay in the Munition field. For a deterministic model, an R^2 value of .999 or greater would be desirable. Given the high level of variability due to the randomness associated with movement by the Red agents through each simulation, an R^2=.92 from the CCD test matrix indicates a very good fit. To develop the Dual Response Surfaces for use in optimization, the data from the CCD test matrix, Time Delay in Obstacle results, was used. The R^2=.868 from the LHS test results is slightly lower, a not unexpected result. According to some recent work by Giunta, et.al, the LHS has been shown to yield results that are not as close of a fit as those from a response surface developed through the use of orthogonal arrays for samples of the same size [12].

Table 5: R^2 Values for Measures of Effectiveness for CCD and LHS

	CCD Regression		**LHS Regression**	
	R^2 Mean	**R^2 Std Dev**	**R^2 Mean**	**R^2 Std Dev**
Time Delay in Obstacle	*.917*	*.783*	*.868*	*.824*
# Enemy at the Obj	.646	.537	.735	.726
# Enemy Killed in MF	.669	.665	.699	.615

The math model developed from the regression is thus shown in Eqn 6. For the maximum standard deviation, 80 time steps was selected since it was close to the average for the lowest standard deviation shown from the X-Pattern munition field.

$$\text{Maximize: } y_\mu=280.64-31.76*b_1+24.86*b_2-29.32*b_3+11.84*b_1*b_2-4.31*b_1*b_3-6.62*b_2*b_3+9.29*b_1^2-23.25*b_2^2+52.49*b_3^2 \quad (6)$$

subject to: $-1\leq b_1\leq 1$ (Coded Width)
$-1\leq b_2\leq 1$ (Coded Depth)
$b_3 \in \{-1, 0, 1\}$ (Coded Pattern)
$y_\sigma\leq 80$ time steps

where, $y_\sigma=78.09-20.32*b_1-6.80*b_2+3.76*b_3+8.43*b_1*b_2-6.55*b_1*b_3-2.48*b_2*b_3+3.59*b_1^2-6.91*b_2^2+22.11*b_3^2$

Using a conjugate gradient method with quadratic estimates to optimize the system yields the optimal design shown in Table 6 [11]. This supports what the initial results showed in terms of a strong performance for the Row munition field pattern.

Table 6: Optimization Results from Equation 6

	Optimized Values	**Converted Values**
Width	.579	1145m
Depth	1	1250m
Pattern	-.926	Row Pattern

Table 7: Predicted Output vs Confirmation Test Results

	Predicted	**Confirmed**
Mean Delay Time (time steps)	354.48	360.13
Standard Deviation (time steps)	80.00	70.80

Using these optimized values with Eqn 6, yields the predicted results shown in the first column of Table 7. A

confirmation experiment of 30 trials was run and analyzed based upon the optimized settings. The results are shown in the second column of Table 7. This is a very close outcome with the confirmation value at the mean within 1.6% of the predicted value. If this had been a deterministic simulation, one would expect a much closer result if the math model was indeed a good fit. For a simulation based upon such variability, this response surface provides a very good fit. As expected there is a greater difference for the standard deviation.

5. CONCLUSIONS

Based upon the results of 15 experiments with a total of 450 trials using the MANA software, it is clear that both the MANA software and the response surface developed herein offer insight into the interaction between combatants and intelligent munitions that are emerging to adorn the battlefield.

For the specific case study used in this paper, the current X-Pattern munition field does not appear optimal. Two better options present themselves from a doctrinal perspective. If there is time, and the risk is acceptable to place the munitions in a patterned munition field, one would get better performance from a Row pattern as tested herein. If there is not enough time or the risk to exposed troops is too great, a field established by random scatter will still offer better results than the X-Pattern minefield. Not only do the simulations point to better than or equal performance using a random scatter method, but the time to emplace the field is much less if scattering the munitions randomly compared to a well-defined pattern. This time savings in emplacement could save a lot of lives. It currently takes about 1.1 hours for two squads to emplace a 1km square disrupt munition field consisting of 20 munitions without the time required to prepare the munitions for emplacement. Since disruption munition fields are usually placed farther forward in a defensive plan, generally more security is required to overwatch the squads emplacing the munitions. In any case, aerial or artillery delivery would provide reduced time for emplacement and yield the desired random scatter. Since future versions of the WAM include a DA-WAM version capable of aerial or artillery delivery, this should become the preferred method of delivery for large area disruption with little time or higher risk. Likewise, systems mounted on existing ground-scatterable munition systems like Volcano may approach the effectiveness of the Row pattern as the delivery would be closer to the row emplacement pattern.

Although the study was very limited in scope, it does offer insight into the interaction between intelligent munitions and ground forces arrayed against those munitions. While the MANA software as written was useful in conducting this initial study, agent-based modeling software designed to handle the specific scenarios developed herein should yield more accurate results. Further study would be useful to extend this work for munition fields and/or any munition that relies upon a sensor/shooter link.

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